# A procedure for the model-based, vibrational diagnosis monitoring of rotating machines

**Abstract**

In a procedure for the vibrational diagnosis monitoring of rotating machines, it is possible to make a more exact determination of the relationships between the vibrational behaviour of the machine and operating parameters, with a reduction in cost. This is achieved by a model-based procedure which comprises a plurality of model-forming steps.

**Description**

This invention relates to a procedure for the model-based, vibrational diagnosis monitoring of rotating machines.

The main task of a procedure for the vibrational diagnosis monitoring of the state of rotating machines is to facilitate an evaluation of the current machine state, of the loading of the machine and of any change in the machine state, if possible without stopping operation. In this connection, the term “machine state” is to be understood as the assessment of the technical state of the machine based on the totality of the current values of all the vibrational quantities and operating parameters. The vibrational quantities are all the characteristic quantities which can be derived from vibration versus time functions, for example the effective value of the vibration rate or the peak value of the rotational frequency vibrational amplitude component. Example of operating parameters include the rotational speed, output, energising current, temperatures and pressures.

An evaluation of the machine state in which a qualitative statement is made on the technical state of the machine is effected by analysing the measured vibrational quantities with the inclusion of the operating parameters.

A procedure of this type, which is particularly suitable for use on steam turbine sets, gas turbines, turbo-pumps, turbocompressors and hydraulic motors, is known from the document "VIBROCAM 500, Das System zur diagnostische Überwachung von Turbomachinen *[A system for the diagnostic monitoring of turbo-machines]*, C081" of Carl Schenck AG.

Together with the bearings and the foundation, the rotors of the aforementioned machines form a complex spring-mass system. The vibrational behaviour strongly depends on the operating regime, on the type of operation, on the operating state and on the setting parameters of the machine, so that individual vibrational quantities, which depend on the type of operation, on the operating regime and on the operating state, are determined for each individual measuring point of each machine, and have to be taken into account for the assessment.

The expression "type of operation" should be understood to be the operating modes of the machine between which a distinction has to be made in principle, such as high speed running, normal operation and idling. Within a given type of operation, an operating regime distinguishes between different possible modes of operation, such as turbine operation, pump operation, and phase shift operation for pumped storage sets in hydroelectric power stations. The operating state is characterised by the values of the significant operating parameters in the operating regimes.

Changes in vibrational behaviour can be caused, for example, by wear and damage, by overload and deformations, by defects in the normal mode of operation and by effects due to the electrical mains. The causes of vibrations are essentially characterised by their phenomenological features. In this connection, the highest information content is provided by the frequencies of the dominant signal components in the vibrational spectrum, and by the frequencies of the signal components for which changes occur.

In the known procedure for vibrational diagnosis monitoring, the vibrational quantities and operating parameters are first determined for the operating regime and operating state concerned, accompanied by a frequency analysis and the formation of characteristic quantities which characterise the vibrational behaviour and changes in it. The normal range and the normal behaviour of the selective characteristic quantities within the range of variation of the operating parameters for all operating regimes and operating states are subsequently determined in a learning phase. This is then followed, in a subsequent step, by a comparison of the limiting values of the current selective characteristic variables with the corresponding characteristic variables of the normal state, so that alarms can be triggered if necessary, or incipient critical machine states can be signalled in good time.

In addition, a procedure for the vibrational diagnosis monitoring of rotating machines, particularly thermal turbo-machines, is known from DE 37 25 123. In this procedure, the signal components which are harmonics of the rotational frequency are determined as vibrational quantities for different states and are stored in a pointer memory. The arithmetic mean for each signal component is subsequently stored in a reference value memory. The difference between the current state and the average reference state is then determined in a monitoring module and is compared with the normal range. In addition, the associated

operating parameters can be determined for the corresponding measuring point. With the aid of these measured data, a function which is capable of predetermining the reference value depending on the operating parameters is then prepared in a regression unit.

The aforementioned procedure for the vibrational diagnosis monitoring of rotating machines results in what is only an inadequate determination of the relationships between the vibrational behaviour of the machine and the operating parameters. Moreover, a multiplicity of limiting values has to be predetermined for the vibrational quantities of the different operating regimes and operating states, which results in a large amount of data and in a considerable operating cost.

Based on this known prior art, the underlying object of the present invention is more accurately to determine the relationships between the vibrational behaviour of the machine and the operating parameters, with a reduction in cost, in order to improve the monitoring and evaluation of the machine state.

This object is achieved by the features given in claim 1.

With the procedure according to the invention for the model-based, vibrational diagnosis monitoring of rotating machines, it is possible to determine and to display the dependencies of vibrations on operating parameters in an automated manner. This not only results in a considerable reduction in the amount of data compared with that which had to be stored for the previous monitoring method, but also provides a better conclusion regarding the causes of vibrations. Changes in the machine state are recognised better. By optimising the adjustment of the machine operating parameters, it is possible to operate machines with a reduced level of vibration.

In a further development of the concept of the present invention, provision is made for a just few characteristic values or for a single characteristic value to be predetermined for all operating regimes and all operating states for the evaluation of the relative deviation of the vibrational quantities. A drastic reduction in the number of limiting values for monitoring the machine state which would otherwise have been necessary is thereby achieved.

The present invention is explained in more detail with reference to the vibrational diagnosis monitoring of a pumped storage set.

The drawings are as follows:

Figure 1 is a schematic illustration of the shaft train of a pumped storage set, showing the measuring points and the data processing unit;

Figure 2 is a block flow diagram of the learning phase; and

Figure 3 is a block flow diagram of the operating phase.

The shaft train 1 of a pumped storage set, with measuring points for vibrational measurement, is schematically illustrated in Figure 1. Sensors 2, 3 for determining vibrational signals are associated with the bearings and with the measurement planes for shaft vibration measurements. The vibrational signals which are determined at the measuring points via the sensors 2, 3 are transmitted to a data processing unit 4 (illustrated by arrows 5). Simultaneously, a reference signal 3″ (one pulse per machine revolution) is derived from the shaft train 1 by means of reference sensors 3′ and is fed to the data processing unit 4. In addition, a multiplicity of sensors is provided which determine various operating parameters such as output, energising current, pressures and temperatures, for example. The measuring signals for the operating parameters are also transmitted to the data processing unit 4 (illustrated by arrows 6). In the data processing unit 4, vibrational quantities 5′ are determined from the vibrational signals 5 and optionally from the reference signals 3″ and are stored or are temporarily stored. Simultaneously, the measured values of the operating parameters 6′ are also stored.

The learning phase, which is schematically illustrated in Figure 2 and in which model formation is effected in a plurality of stages, forms the basis of the model-based procedure for vibrational diagnosis monitoring according to the invention.

The first aim of model formation is to determine whether all the operating parameters which have a decisive effect on the vibrational behaviour of the machine have been determined metrologically. This can be checked by predicting vibrational quantities from the operating parameters alone. It is possible to determine the vibrational quantities sufficiently accurately from the values of the parameters using a simple mapping specification, so that the sought-after information is represented in the data. For this purpose, the following expression is employed:

$$\hat{y}_i = \hat{F}(x_i)$$

where F denotes the model function. One possible formulation for F is a linear combination of nonlinear base functions, amongst others. The model for a data point of target size $y_i = y(it_s)$ ($t_s$ = scanning time) for an arbitrary state vector $x_i$ is then given by

$$\hat{y}_i = \sum_j^M a_j X_j(x_i)$$

where $X_j$ represents a base function of the model.

In the learning phase, all the measured operating parameters 6′ which are stored in the data processing unit are firstly transmitted to a forward selection unit 7. In addition, the vibrational quantities 5′ are determined. A linear prediction model is first of all assumed, which maps the operating parameters 6′, which are combined to form the state vector $\chi(i) = (x_1(i), x_2(i) \ldots x_d(i)$ on to the vibrational quantities $y(i) = (y_1(i), y_2(i) \ldots x_1(i); i = 1, 2 \ldots N$, by a linear combination of the components of the operating parameters. This is followed by an assessment of the vibration-determining operating parameters for relevance, which is effected by a forward selection procedure which is described in detail below.

The selection of the vibration-determining operating parameters is thus fed back to a model structure determination problem, since the individual operating parameters can be determined as terms of a model, and those terms which result in the optimum model can be selected by means of term selection procedures. Only the operating parameters which are identified in this manner as being relevant to the predetermination of the vibrational quantities are fed as input quantities 8 to a polynomial generator 9. A more complex model, which is thus a more powerful one, is determined in the polynomial generator 9. Complex models can be generated by the inclusion of power terms and of product terms. These models

are called polynomial models. The selection of the optimum model terms from a predetermined upper set is again a form of model structure determination, and is effected by forward selection. In the following forward selection unit 11, the structure of the model is determined from the vibrational quantities 5′ and from the base function 10 provided by the polynomial generator 9. This is followed by determining the optimum parameters $a_j$ by minimising the sum of the squares of the model errors:

$$\chi^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

in the following least square parameter estimation unit 13 with the aid of the input vibrational quantities 5′ and the selected base function 12. This gives a system of linear equations, the solution of which gives the sought-after model parameters 14.

The model structure is determined by the forward selection procedure, which is described below and which is carried out in the forward selection units 7 and 11. That quantity which most reduces the mean square error $\chi^2$ is added step-wise to an initially empty set of operating parameters. This results in a ranking which shows which operating parameters most strongly influence the vibrational quantities. The more the operating parameters which are taken into consideration, the smaller the mean square error $\chi^2$ becomes. However, the latter still only relates to the data from the learning phase (test data). On its own, therefore, the mean square error $\chi^2$ is unsuitable for the selection of relevant terms.

A necessary statement here is provided by an assessment of what is termed the predicted error of the test data. This shows how accurately the trained model makes predictions for future, unknown data. If sufficient sets of data are present from the learning phase, this can be effected by dividing the data into a training data set and a test data set.

Another possibility consists of employing a very much more efficient method, which is known in statistics and which is termed "cross-validation" (B. Efron and R.J. Tibshirani: "An Introduction to the Bootstrap", Chapman and Hall, 1993). In this method, a plurality of divisions is made in the training and test data sets. One extreme variant of this is to divide the N data points into a training data set of magnitude N-1 and a test data set of magnitude 1. This procedure is termed "leave-one-out (LOO) cross-validation". The selection criterion $\sigma^2$

is then given by the average of the mean square errors when predicting the sets of test data which are left out.

If $F_i(x_i)$ is the prediction for the i-th data set after the model has been trained with the other N-1 data sets, the test data error $\sigma^2$ is then given by:

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{F}(x_i))^2$$

The advantages of this method are firstly that there is no effect on the mean value due to the division into training and test data sets, and secondly that the entire training and test data set can be used for training.

In contrast to the mean square error $\chi^2$, which indicates how well the model prediction agrees with the training data, $\sigma^2$ is a measure of the agreement for unknown data sets. The $\chi^2$ function which was introduced previously decreases monotonically with an increase in new base functions, and is therefore unsuitable for the selection of relevant terms. However, the LOO error $\sigma^2$ first decreases with the incorporation of new base functions and then increases again above a critical number, since the error between the data sets of the training set increases (overfitting). This property is used for the selection of relevant terms.

After a restriction to just a few quantities 8 has been made in the forward selection unit 7 by the selection of suitable operating parameters, renewed model formation can be effected with the latter in the polynomial generator 9, in which a nonlinear model, which is thus more powerful, is utilised. This model then provides the desired functional relationships between vibrational quantities and operating parameters.

For thermal turbo-machines, the two terms effective output *(P(t))* and energising current *(I(t))* often have the greatest relevance.

The general expression for a second order polynomial is:

$$\hat{s}(t) = a_0 + a_1 P(t) + a_2 P(t)^2 + a_3 I(t) + a_4 I(t)^2 + a_5 P(t) I(t) = \sum_{j=1}^{6} a_j X_j(P(t), I(t))$$

Selection of the relevant terms within this model is again effected by means of the forward selection procedure described above, in the forward selection unit 11, and provides a

compact, formula-based relationship (hereinafter denoted as optimised model 2) between vibrational quantities and operating parameters:

$$\hat{s}(t)=a_0+a_1P(t)+a_1I(t)^2$$

Determination of the values of the model parameters $a_0$, $a_1$ + $a_2$ 14 is effected in the least square parameter assessment unit 13.

When model identification and formation from the learning phase is complete, the operating phase of the procedure commences. The operating phase is schematically illustrated in Figure 3. In the latter, it is only the previously selected operating parameters 8 which are supplied to the model 12 which has been optimised in the learning phase. Prediction of the vibrational quantities according to the model formulation described above is then effected in the computing unit 15, taking into account the optimum model parameters 14 which are also fed to the computing unit 15. The predicted vibrational quantities 16 are fed to a comparator unit 17. In addition, the currently measured vibrational quantities 5″ are fed to the comparator unit 17.

At any point in time, a comparison of the predicted vibrational quantities 16 with the vibrational quantities 5″ which are currently measured provides a measure of the correspondence between the machine and the model, and is thus relevant for the diagnosis. At the same time, the magnitude of the relative deviation is a measure of significant changes in the machine state. This value can be fed, as an initial value 18 from the comparator unit 17, to a limiting value comparator unit 19. In the limiting value comparator unit, the selective deviation 18 is compared with the predetermined limiting values 20. The latter may comprise just a few relative limiting values or may be a single relative limiting value only. If the relative deviation 18 exceeds the predetermined limiting values 20, a signal 21 is emitted. This can be used for an alarm message or for data archiving.

In a further embodiment, the procedure according to the invention which has been described above is suitable for providing relationships which are valid within operating phases of the same type. Examples of the latter include full load phases, light load phases or defective states. This makes it necessary to divide the data set into natural classes, which can be effected in an automated manner here. For this purpose, the operating parameters are

subjected to a fuzzy C means clustering procedure (M.P. Windham "Geometrical fuzzy clustering algorithms", Fuzzy Sets and Systems, 10; 271-279, 1983). This procedure results in the division of the data into n classes, where n has to be appropriately predetermined depending on the specific application. This procedure involves the segmentation of the time domain into segments in which a substantially stationary operating phase exists. Modelling is then continued within the segments, and provides separate relationships for each operating phase. This has the advantage that it is possible to identify dependencies which only exist in one or in some operating phases, and methods of treatment can be derived specially for these operating phases (e.g. the full load phase).

**Claims**

1. A procedure for the model-based, vibrational diagnosis monitoring of rotating machines, wherein vibrational quantities and operating parameters are first of all determined and stored in a learning phase and model formation is subsequently effected in a plurality of steps, wherein first of all, with the aid of a simple model, for example a linear model, the operating parameters which are combined to form the state vector x(i) are mapped, by a linear combination of the components thereof, on to the vibrational quantities y(i) and by comparing the measured vibrational quantities with the predicted vibrational quantities a check is first made of whether all the quantities relevant to vibration have been determined, an assessment is subsequently made of the ranking of the operating parameters for relevance by means of a forward selection procedure, model formation is then effected with a complex model by means of selected, relevant operating parameters, and a renewed assessment is then made of the ranking of the operating parameters for relevance by the forward selection procedure, so that a functional relationship based on a complex model can be derived between selected relevant operating parameters and vibrational quantities, current vibrational quantities and operating parameters are determined in a subsequent operating phase, and significant changes in the machine state can be ascertained by assessing the relative deviation of the currently measured vibrational quantities from the vibrational quantities predicted by the model.

2. A procedure for vibrational diagnosis monitoring according to claim 1, wherein in the forward selection procedure the relevant operating parameters are determined by minimising the sum of the squares of the model errors.

3. A procedure for vibrational diagnosis monitoring according to claim 1, wherein the forward selection procedure for determining the relevant operating parameters is terminated by the leave-one-out cross-validation procedure or by other cross-validation procedures.

4. A procedure for the vibrational diagnosis monitoring of rotating machines according to claim 1, wherein the significant changes are displayed and evaluated and are used for alarm messages, data storage and for shutting off the machine.

5. A procedure for the vibrational diagnosis monitoring of rotating machines according to claim 4, wherein if after evaluating the significant changes it can be concluded that there are abnormal or impermissible machine states, a change is made to the relevant operating parameters based on the knowledge of the functional relationships between the relevant operating parameters and predetermined vibrational quantities.

6. A procedure for the vibrational diagnosis monitoring of rotating machines according to claim 1, wherein for all machine states just a few characteristic values or a single characteristic value are/is predetermined for the evaluation of the relative deviation.

7. A procedure for the vibrational diagnosis monitoring of rotating machines according to claim 1, wherein the data are subdivided into stationary segments.

8. A procedure for the vibrational diagnosis monitoring of rotating machines according to claim 7, wherein subdivision is effected using fuzzy C means clustering.

9. A procedure for the vibrational diagnosis monitoring of rotating machines according to claim 8, wherein model formation is effected for each of all the stationary segments, so that for each of all the stationary segments a functional relationship based on a complex model can be derived between relevant operating parameters and vibrational quantities.